# COVER SHEET

# Mobility Enhancement and Assessment for a Visual Prosthesis

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## ABSTRACT

This paper investigates methods of processing mobility related static images to enhance the effectiveness of a visual prosthesis system. Eight images were processed into 50x50 pixel binary, greyscale, Sobel and Canny edge detected images. 10 subjects were asked 5 mobility related identification tasks for each (randomly ordered) image. Results indicate that edge detection may be useful at this resolution. However, there was not a significant difference found between the results achieved using the Canny and Sobel algorithms. These results support the development of an adaptive device. A mobility display framework has been proposed to assist in this development. Future work will focus on processing image sequences and the development of a visual prosthesis simulation device.

**Keywords:** Artificial human vision, visual prosthesis, blind mobility, image processing

## 1. INTRODUCTION

It is possible to partially restore some sight to the blind by sending electrical impulses to the human visual pathway. When an impulse is received by a blind person they may perceive one or more points of light ('*phosphenes*'). A number of research teams are currently pursuing research into visual prosthesis systems using this method. In such a system, image processing will provide the link between a camera and an implanted electrode array and is therefore an integral part of all clinical visual prostheses [1]. A successful visual prosthesis should result in increased mobility performance. Evidence from previous research suggests that the objective assessment of mobility is important in developing and comparing different devices and techniques. This section provides an overview of mobility assessment and mobility aids, followed by a brief review of image processing approaches which may be useful for a visual prosthesis system.

### 1.1 Blind Mobility

In 1997 the World Health Organization estimated that there were close to 150 million people with significant visual disability worldwide, with 38 million of those people blind [2]. Blind Mobility is commonly defined as a person's ability to travel between locations "gracefully, safely, comfortably and independently" [3]. Blind mobility requires skill, effort and training. Mobility problems for a blind person can be caused by changes in terrain and depth (stairs, kerbs); unwanted contacts (bumping); and street crossings (which involve judging the speed and distance of vehicles and may involve identifying traffic light colour) [4]. The most dangerous events for a blind or partially sighted person are drop offs (sudden depth changes, such as on the edge of a subway platform) and moving vehicles [5]. Making unwanted contact with pedestrians is also undesirable as it can be socially awkward and may pose a threat to a person's safety [6].

The three main methods used for assessing mobility are self report questionnaires, field experiments (such as walking through a shopping mall) and artificial laboratories (such as walking through an artificial maze). The latter two methods usually involve a count of the frequency of obstacle contacts by a subject and their walking speed (usually the percentage of preferred walking speed). The assessment of mobility provides information on the effectiveness of different training techniques and also provides information for developers and consumers of mobility devices.

### 1.3 Mobility information presentation modes

Mobility devices generally provide information by tactile or auditory methods. Ambient sound (for example, voices or directional traffic noise) is important in blind mobility (as it is in sighted mobility). Non-visual information may also be

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tactile (such as Braille) or olfactory. A visual prosthesis device differs from traditional mobility aids as it uses a functioning component of the visual pathway, and does not overload another sense.

### 1.3.1. Traditional blind mobility devices

Experience and benefits from existing mobility aids could be useful for the design of a visual prosthesis. The most useful current mobility aids are the guide dog and the long cane.

The long cane provides a blind person with sufficient information for safe movement in the immediate environment. Mobility enhancement in a blind person after long cane training is often dramatic [7]. An additional benefit is the high visibility of the cane to drivers and other pedestrians. The most significant problem with the long cane is that it provides a preview distance of only two paces. Because there is limited preview, a long cane user needs fast reaction times. A cane does not protect against obstacle collision to the upper part of the body (such as wall-mounted public telephones). There is also a risk of tripping other pedestrians with a cane [8].

Guide dogs also provide good mobility assistance by pulling in the same way that a human guide would. They are able to respond to hand and voice signals and are trained to avoid obstacles, prevent veering in street crossings, stop if there is a dangerous situation and intelligently disobey commands that are not safe. A dog may remember common landmarks (such as a particular shop door). However guide dogs are not suitable for people who are not comfortable with dogs, are not physically fit or cannot maintain a dog [9].

Electronic Travel Aids (ETA) provide tactile or auditory information to a blind traveler about their immediate environment. These devices usually use ultrasound (such as the UltraCane [10]) but may also use a laser [11] or image processing [12] approach. Although a number of ETA's have been developed, none has achieved widespread market penetration. These devices often provide little benefit in mobility, are expensive and may be cosmetically unattractive [7]. A review of ETA requirements is provided in [13] and a list of available ETAs is provided by [14]. Another approach to blind mobility and navigation involves adjusting the environment to provide useful information, such as the Talking Signs system, widely implemented in San Francisco [15].

### 1.3.2. Visual Prosthesis devices

The three main approaches to visual prostheses involve a cortical implant, retinal implant (subretinal or epiretinal), and an optic nerve cuff electrode. An overview of these approaches is provided in [16] and a good review is [17]. Each approach has advantages and disadvantages, and all have been successful in providing phosphene perception to subjects. Although visual prosthesis systems should eventually provide valuable mobility information, there are currently a number of constraints including:

- ***Phosphene perception***. Current technology limits the number of phosphenes that can be provided to a patient. A demonstration of the effect of reduced visual information is presented in Figure 1. Therefore it is necessary to develop image processing methods for the optimal use of these phosphenes. Additionally, the size, shape and brightness of phosphenes are not currently predictable.
- ***Real-time processing:*** Real-time performance has been problematic for other image based mobility systems ([18-24]), particularly those that are stereo-vision based. One way of providing real-time processing may be to restrict the field of view of the camera, although this may restrict the amount of preview (or time to anticipate problems) available to a blind traveler. Movement of the subject (egomotion) is an additional image processing overhead, as the camera will need to be attached to the person's body. Parallel hardware architecture and code optimization techniques could also enhance processing performance.
- ***Integration:*** The integration of different functions is a challenge. Dangerous features of the environment, such as moving objects, obstacle detection and sudden changes in depth, should be displayed with a higher priority than less important information.
- ***Context:*** Scene understanding depends to a large extend on context. Different display and processing modes will probably be required for a prosthesis system to cope with differences in operational environments.
- ***Device simulation.*** Currently it is necessary to use a visual prosthesis simulation with normally sighted subjects. The results of these investigations may not generalize to actual visual prosthesis patients.

**(a) (b) (c)**

**Figure 1: Demonstration of the reduced visual information for a visual prosthesis: a, a street scene image; b, street scene reduced to a resolution of 25x25 pixels; c, a 25x25 simulated phosphene representation of the street scene**

### 1.4 Image processing methods for prosthesis information presentation

The use of image processing could enhance the effectiveness of visual prosthesis systems. We can use an information reduction approach to provide essential environmental information, and/or attempt to understand objects in the environment. Most existing visual prosthesis efforts are aimed at the information reduction level, which is concerned with the reduction or collapse of visual information. Edge detection is a useful method of encoding and describing information from an image in a more economical form, and involves identifying image contours where the brightness of the image changes abruptly [25]. Cortical prosthesis research by the Dobelle Institute has found that Sobel edge detection and image reversal enhance the ability of subjects to recognize important scene components (such as doorways) [1]. Operations on images at the information reduction level are designed to improve image saliency, or to emphasize features of particular importance or relevance, for example kerbs or walls.

A different approach involves attempting to understand components of the scene. This scene understanding level is concerned with identifying features and extracting information. The scene structure is still there to a degree, but it is idealised or reduced. An example application might be to identify a bus stop, fire hydrant or traffic light. It may also be useful to know the distance to the object (number of steps, or time at current walking speed). Due to the limited number of phosphenes that can be generated by current technology, it may be better to present a symbolic representation. For example a small part of the grid (perhaps 5x5) could be used for information on obstacle locations in the current environment. Auditory Information could also be provided in natural language, for example "A door is located forward to the right". A scene description mode could be useful (similar to [23]).

Previous work at our facility [26], [27] has examined the use of various image processing techniques (such as enhancing edges, using different grey scales and extracting the most important image features) to identify a recognition threshold for low quality stationary images. These images are used to represent the limited number of phosphenes available to the subject (typically a 25x25 or 50x50 array, with limited greyscales). This research aims at providing a means of determining which parts of a visual scene to represent, and a model for inherent information to determine which visual elements of the scene should be presented for maximum perceptual intelligibility by the subject. This work has suggested that object recognition is dependent on image type and that adaptive methods will be required for a functioning prosthesis system This research has found that higher resolution is more important than increased grey scale and that faces are more recognizable at lower resolution than other objects (such as chairs or doors) [28].

### 1.6 The Current Study

The purpose of the current study is to investigate methods of processing typical mobility related images at a resolution of 50x50 pixels (representing a 50x50 phosphene array). Previous research has indicated that edge detection is not very useful at low resolution (25 x 25 or below) (see [26]): this study aimed to determine if edge detection is beneficial at the higher resolution. The Sobel method of edge detection is typically used for visual prosthesis image processing research.

Another widely used method is the Canny operator. In this study we also intended to test if the Canny operator achieved higher object identification results than the Sobel operator for mobility related images. We also aimed to investigate if different scene types affected the identification of mobility information.

## 2. METHODOLOGY

### 2.1 Images

We are currently developing a visual prosthesis simulation device which utilizes an Intel XScale PXA255 based PDA with a Pretect VGA CompactCamera installed [29]. The CompactCamera is capable of a minimum 12 frames per second at a resolution of 160x120; therefore we based this research on images with this resolution. For this study, we have assumed that a prosthesis device is capable of displaying a 50x50 pixel resolution.

**Figure 2: Mobility related images used in this study (top left to right: images 1 to 4. Bottom row: images 5-8)**

This study consisted of eight mobility-related images, shown above. These images were either captured by the author using the Pretect CompactCamera (images 1, 7 and 8) or resized to 160x120 from mobility-related images obtained from web searches (images 2,3,4,5 and 6). Four experimental images (binary, greyscale and Sobel and Canny edge detected) were processed from each of these base images (creating a test set of 32 images). The stages of processing are summarized in Table 1 below. Edge detection sensitivity thresholds, resulting in the most accurate representation of mobility information, were (subjectively) selected for each image (see Table 2). For Canny edge detection, the standard deviation of the Gaussian filter (sigma) was equal to 1 for all images. In addition, the edge images were dilated using a flat, disk-shaped morphological structuring element, which helped to retain the edge information after the image was resized. Finally, a 3x3 neighborhood median filter was applied to each image to soften the pixelization effects after resizing the images. All image processing was conducted using the Matlab Image Processing Toolkit.

**Table 1: Image processing steps applied for each image type (Binary, Canny, Greyscale and Sobel)**

| Image Type 1 | Image Type 2 | Image Type 3 | Image Type 4 |
|---|---|---|---|
| Greyscale conversion | | | |
| Binary conversion | Edge detection (Canny) | | Edge detection (Sobel) |
| | Line enhance | | Line enhance |
| Resize image to 50x50 | | | |
| Resize image to 256x256 | | | |
| Apply median filter | | | |

**Table 2: Image edge detection and line enhancement thresholds**

| Image | Sobel Sensitivity Threshold | Canny Sensitivity Threshold | Dilation Disk size |
|---|---|---|---|
| 1. Child on street | .09 | .30 | 2 |
| 2. Path near road | .18 | .45 | 1 |
| 3. Person in office | .14 | .45 | 1 |
| 4. Person in bathroom | .16 | .40 | 3 |
| 5. Sparse office | .17 | .60 | 2 |
| 6. Streetscene with tree | .10 | .45 | 1 |
| 7. Phone booth obstacle | .14 | .35 | 2 |
| 8. Railway platform | .17 | .40 | 1 |

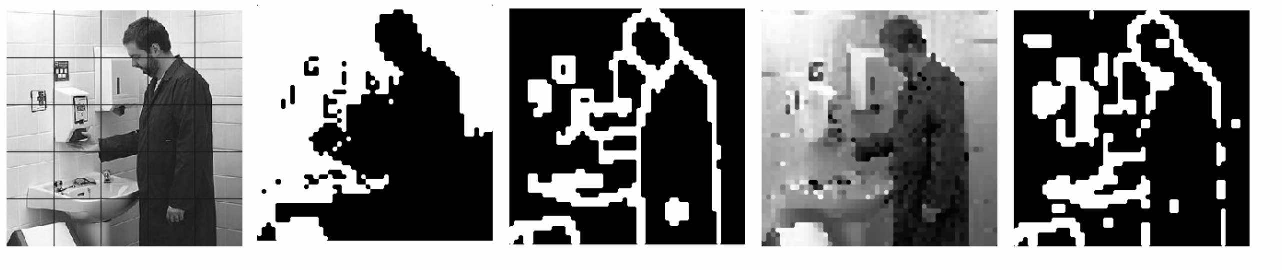

**Figure 3: Image Processing on image 4: a. Original image with 5x5 grid overlaid; b. Binary; c. Canny edge detection; d. Greyscale; e. Sobel edge detection**

### 2.2 Questions

Each subject was required to respond to the following five questions for each image:

1. Can you identify a person in this image?
2. Can you identify a tall obstacle (e.g. pole/tree)?
3. Can you identify a drop off in this image?
4. Can you identify a low obstacle (such as a chair)?
5. Please imagine you are moving through the scene and this image is the only visual information available to you. Where would you aim your next step? Please click on this button and then select the location on the image.

For the first four questions, the subject was required to select a Likert scale rank as follows:

1. Definitely yes
2. Probably yes
3. Maybe
4. Probably no
5. Definitely no

### 2.3 Experimental software

The software for this research was written using Microsoft Visual Basic 6.0 and presented on a laptop using Microsoft Windows 2000. The image presentation sequence was randomized for each subject undertaking the study. If a ranking between 1 (‘definitely yes’) and 4 (‘probably no’) was selected for each question, the subject was prompted to click on the image location which best matched the object referred to in the question. These coordinates were stored and later converted to a 5x5 grid (an example of this grid is shown in Figure 3a). If a subject selected a ranking of ‘Definitely no’, they were not required to click on the image.

### 2.4 Procedure

10 subjects were obtained from volunteer postgraduate students and staff from the Faculty of Built Environment and Engineering at the Queensland University of Technology. Each subject was asked to sit in front of a computer with the experimental software loaded. A definition of a "drop-off" was verbally provided to all subjects and they were then asked to read the instructions on the screen.

### 2.5 Statistical analysis

A matrix of 'correct' grid locations for each image and question type combination was generated (this file consisted of 169 entries). These 'correct' grid locations were compared against the grid locations selected by subjects. Questions one to four were not valid for all images (for example, there are no people in images 5, 6 and 8). Therefore counting matching grid responses does not consider the incorrect identification of image objects. To assist with our analysis, a question ranking of one ('definitely yes') to three ('maybe') was understood to mean the subject had thought they had identified the question-related object. A ranking of four ('probably no') or five ('definitely no') was assumed to mean the subject did not think the question-related object was available in the image. Using these assumptions, we are able to count the number of *correctly* and *incorrectly identified* objects, in addition to *incorrectly not identifying* (there was an object in the image which answered the question, but this was not identified) and *correctly not identified* objects (there was no object in the image which matched the question, and the subject correctly indicated this). These steps are summarized in Table 3.

**Table 3: Steps in identifying correct/incorrect and identified/not identified grid responses**

| Selected Rank (1-5) | Is the question valid for this image? | Is selected image location correct? | Response classified as: |
|---|---|---|---|
| **1,2,3** | Yes | Yes | Correctly identified |
| | | No | Incorrectly identified |
| | No | Yes | N/A |
| | | No | Incorrectly identified |
| **4,5** | Yes | Yes | Incorrectly not identified |
| | | No | Incorrectly not identified |
| | No | Yes | N/A |
| | | No | Correctly not identified |

## 3. RESULTS

In this section we present the results of our experiment. These results fall into three main sections: The Likert rankings selected by subjects; the correct or incorrect identification of objects; and the selected locations for the next step (question 5).

The Likert response of 'Definitely no' comprised 45% of responses to questions 1 to 4, and was highest (60%) for the identification of people (question 1). Subjects were least certain about the identification of low obstacles in images, with 22% selecting a ranking of 'maybe'. These results are displayed in Table 4. Table 5 lists rankings by different image types. Most of the 'definitely yes' responses were related to Greyscale images, which also had the least proportion of 'maybe responses' (9%). The results for binary and edge detected images were similar.

As discussed in section 2.5, the grid locations selected by subjects were divided into four groups: whether the object was identified or not and whether this identification was correct or incorrect. The results for each image type are presented in Table 6. Overall 55% of objects were identified correctly and 45% incorrectly. Only 17% of objects were incorrectly identified ('false positives'). Greyscale images received the highest number of correct responses. Sobel edge detected images resulted in a slightly higher percentage of correct responses than Canny edge detected or binary images. However, the Canny edge images had a lower percentage of incorrect/not identified objects compared to binary and Sobel.

**Table 4: Summary of rankings for each question type**

| | Question Type | | | | |
|---|---|---|---|---|---|
| **Rank** | **1. Person** | **2. Tall Obstacle** | **3. Drop off** | **4. Low Obstacle** | **% of total** |
| **1. Def. Yes** | 14% | 13% | 8% | 13% | 12% |
| **2. Prob. Yes** | 10% | 11% | 11% | 13% | 11% |
| **3. Maybe** | 7% | 18% | 18% | 22% | 16% |
| **4. Prob. No** | 9% | 18% | 15% | 20% | 16% |
| **5. Def. No** | 60% | 40% | 49% | 32% | 45% |
| **Total** | 100% | 100% | 100% | 100% | 100% |

**Table 5: Summary of rankings for each image type**

| | Image Type | | | | |
|---|---|---|---|---|---|
| **Rank** | **Binary** | **Edges (Canny)** | **Greyscale** | **Edges (Sobel)** | **% of total** |
| **1. Def. Yes** | 7% | 5% | 31% | 5% | 12% |
| **2. Prob. Yes** | 10% | 11% | 13% | 12% | 11% |
| **3. Maybe** | 18% | 20% | 9% | 16% | 16% |
| **4. Prob. No** | 19% | 16% | 8% | 19% | 16% |
| **5. Def. No** | 47% | 48% | 39% | 48% | 45% |
| **Total** | 100% | 100% | 100% | 100% | 100% |

**Table 6: Identification results for questions 1 – 4 for each image type**

| **Image Type** | **Object Identified** | | **Object Not Identified** | | **Total** | |
|---|---|---|---|---|---|---|
| | Correct | Incorrect | Correct | Incorrect | Correct | Incorrect |
| **Binary** | 17% | 17% | 33% | 33% | 50% | 50% |
| **Canny** | 17% | 19% | 34% | 29% | 52% | 48% |
| **Greyscale** | 34% | 18% | 31% | 16% | 66% | 34% |
| **Sobel** | 18% | 14% | 35% | 32% | 54% | 46% |
| **Total** | 22% | 17% | 34% | 28% | 55% | 45% |

A summary of responses for each image is presented in Table 7. Image 4 (man in bathroom) and 5 (sparse office) received the highest percentage of correct identifications. Images 2 (path near road), 3 (Person in office) and 7 (Phone booth obstacle) received the lowest percentage of correct identifications. The results for binary and edge detected images appear similar for most images. These results are also presented in graphical form in Figure 4.

**Table 7: Identification results for questions 1 – 4 for all images**

| Image Base | Image Number | Object Identified | | Object Not Identified | | Total | |
|---|---|---|---|---|---|---|---|
| | | Correct | Incorrect | Correct | Incorrect | Correct | Incorrect |
| **1** | Binary | 20% | 15% | 20% | 45% | 40% | 60% |
| | Canny | 30% | 23% | 18% | 30% | 48% | 53% |
| | Greyscale | 55% | 20% | 10% | 15% | 65% | 35% |
| | Sobel | 40% | 15% | 20% | 25% | 60% | 40% |
| **2** | Binary | 3% | 28% | 30% | 40% | 33% | 68% |
| | Canny | 0% | 20% | 35% | 45% | 35% | 65% |
| | Greyscale | 18% | 33% | 23% | 28% | 40% | 60% |
| | Sobel | 3% | 23% | 33% | 43% | 35% | 65% |
| **3** | Binary | 8% | 8% | 20% | 65% | 28% | 73% |
| | Canny | 13% | 13% | 23% | 53% | 35% | 65% |
| | Greyscale | 48% | 13% | 18% | 23% | 65% | 35% |
| | Sobel | 5% | 5% | 25% | 65% | 30% | 70% |
| **4** | Binary | 43% | 5% | 45% | 8% | 88% | 13% |
| | Canny | 48% | 10% | 40% | 3% | 88% | 13% |
| | Greyscale | 50% | 5% | 45% | 0% | 95% | 5% |
| | Sobel | 45% | 8% | 43% | 5% | 88% | 13% |
| **5** | Binary | 15% | 18% | 60% | 8% | 75% | 25% |
| | Canny | 15% | 8% | 68% | 10% | 83% | 18% |
| | Greyscale | 25% | 8% | 68% | 0% | 93% | 8% |
| | Sobel | 13% | 10% | 65% | 13% | 78% | 23% |
| **6** | Binary | 23% | 23% | 30% | 25% | 53% | 48% |
| | Canny | 3% | 40% | 38% | 20% | 40% | 60% |
| | Greyscale | 25% | 25% | 28% | 23% | 53% | 48% |
| | Sobel | 13% | 20% | 38% | 30% | 50% | 50% |
| **7** | Binary | 13% | 28% | 10% | 50% | 23% | 78% |
| | Canny | 25% | 30% | 8% | 38% | 33% | 68% |
| | Greyscale | 30% | 43% | 10% | 18% | 40% | 60% |
| | Sobel | 23% | 28% | 10% | 40% | 33% | 68% |
| **8** | Binary | 15% | 15% | 50% | 20% | 65% | 35% |
| | Canny | 5% | 10% | 48% | 38% | 53% | 48% |
| | Greyscale | 25% | 0% | 50% | 25% | 75% | 25% |
| | Sobel | 8% | 8% | 50% | 35% | 58% | 43% |
| **Total:** | | 22% | 17% | 34% | 28% | 55% | 45% |

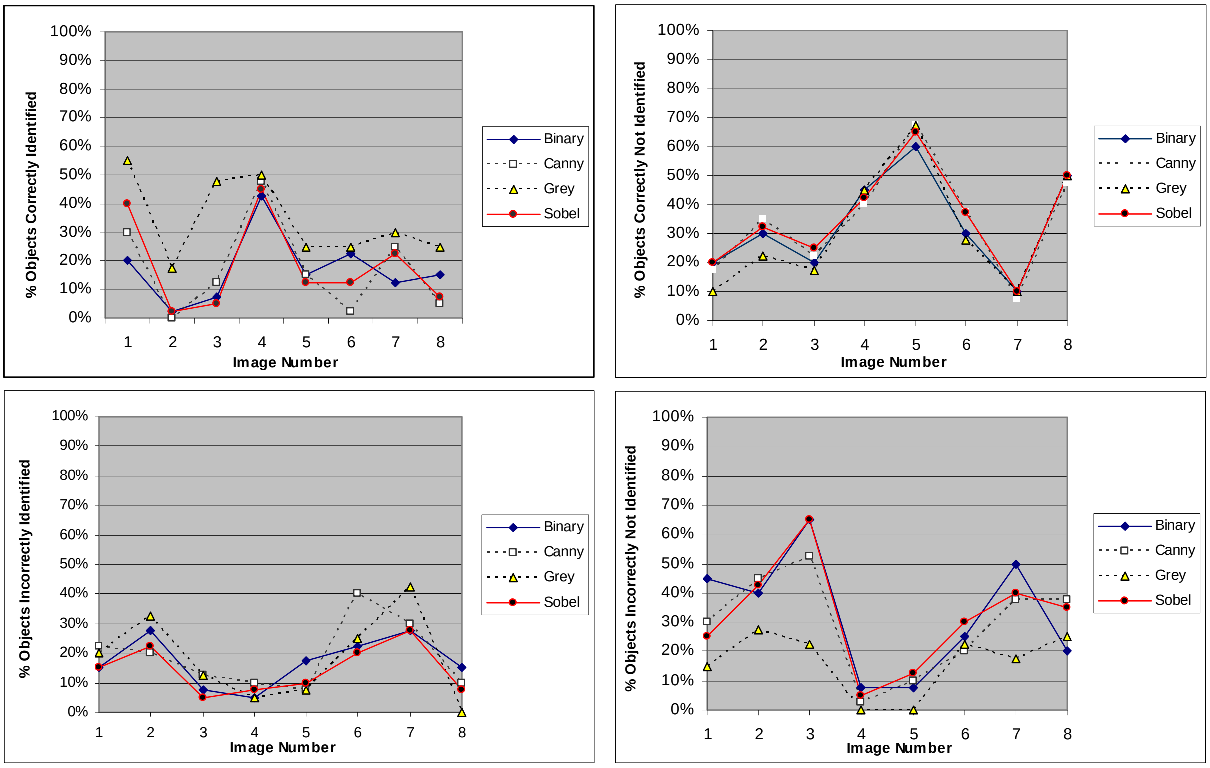


**Figure 4: Identification results for each image**

Question 5 asked subjects to select where they would place their next step. Results for this question (and the 'correct' grid locations) were similar for each image. As shown in Table 8, the greyscale images scored the highest percentage of correct responses to question 5. There was no difference in results between the Sobel and Canny edge detection methods. Binary images received the lowest percentage of correct responses.

**Table 8: Question 5 results for each image type**

| | Image Type | | | | |
|---|---|---|---|---|---|
| | **Binary** | **Edges (Canny)** | **Greyscale** | **Edges (Sobel)** | **% of total** |
| **Correct** | 78% | 84% | 90% | 84% | 84% |
| **Incorrect** | 23% | 16% | 10% | 16% | 16% |
| **Total** | 100% | 100% | 100% | 100% | 100% |

## 4. DISCUSSION AND FUTURE WORK

The purpose of this study was to investigate the benefits of some simple forms of image processing on mobility related static images at 50x50 pixel resolution.

***Is edge detection beneficial for mobility related static images at 50x50 pixel resolution?***

At the 50x50 pixel level edge detection appeared to be helpful in the identification of typical mobility related objects. Overall, edge detection received slightly higher results to a binary image representation. In all images, the greyscale representation received the highest number of correctly identified results. However, as Figure 4 illustrates, the results varied depending on the image (both edge detection methods had lower results than binary for image 6 and 8).

***Does the Canny method of edge detection result in more useful mobility information than the Sobel method at this resolution?***

The Sobel method resulted in slightly better (1%) correct object identifications and 1% higher correct non-identification of objects. The Canny method resulted in a 5% higher incorrect identification of objects than Sobel. Overall, there did not seem to be a significant difference between the results obtained using the Canny and Sobel edge detection algorithms at this resolution. Based on these results, the Sobel method appears more suited to a visual prosthesis system due to its lower computational cost than the Canny method.

***Do different image types affect the identification of mobility related information?***

There were some differences found between image types. The results for images 4 (man in bathroom), 5 (sparse office) and 8 (train platform) were significantly higher than other images. These images are less cluttered, and the main object in each image is centered. Images 2, 3 and 7, which do not have the main objects centered, received the worst results. The original resizing of images to 160x120 pixels may also have contributed to these results.

The results for the 'next step' question (Table 8) were high for all image types. This indicates that a greater range of mobility related images (such as doorways or stairs may be required. The results did suggest that the use of edge detection is a useful method at this resolution for this task.

The results from this paper support the development of an adaptive system. The display from a visual prosthesis could use different information reduction and scene understanding information methods depending on the task context and the type of scene. For mobility purposes this display depends on three main dimensions of the current scene (Figure 5):

- ***Context:*** The type of scene can affect the type of image processing required. For example, there may be a greater need for information reduction in a crowded shopping mall than a suburban street.
- ***Task:*** Different information is required depending on the current task. A road crossing task may emphasize a straight path to the opposite kerb (to prevent veering), whereas a task involving identifying a set of keys on a cluttered table may involve zooming or object recognition.
- ***Alert**:* The system needs to continually investigate any hazardous features of the current scene. These alerts, such as an approaching tree branch (obstacle detection) or descending stairs (drop off) should run as background tasks, and interrupt the current display when required.

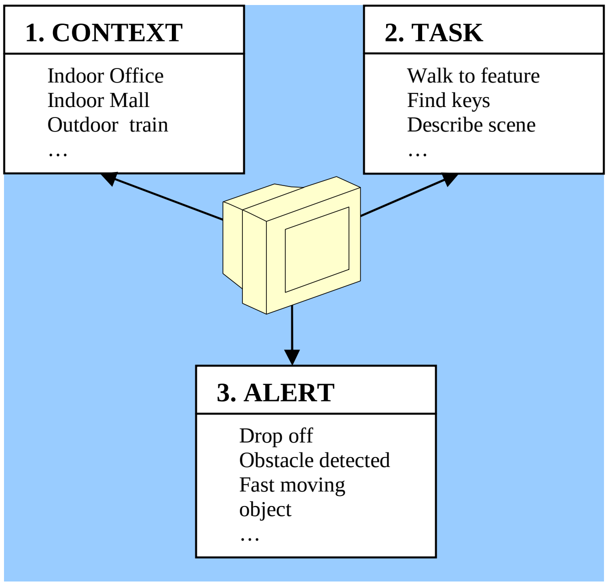


**Figure 5: Proposed mobility display framework**

To investigate the mobility display framework shown in Figure 5, we are developing a visual prosthesis simulation. This portable head mounted device which consists of a Personal Digital Assistant (PDA) and an attached digital camera. Currently the PDA display is used to present the phosphene simulation. A normally sighted subject can then wear the device and be assessed on various mobility tasks under different contexts, alert scenarios and image processing conditions. A sheet of material is used to limit the subject's visual information to the PDA display. Further details of this simulation are available in [29]. A similar simulation approach was used in [30] where the minimum number of phosphenes required for adequate mobility was found to be 25x25 with a field of view of $30^o$.

The use of static images in this study simplifies the mobility task. It should be possible to use a lower pixel resolution when a subject is able to use ego and object motion to assist with object identification: Cha et al [30] found that head movements were important in improving mobility performance at 25x25 resolution. Applying an ecological approach to visual prosthesis development could emphasize this movement in a complex and changing environment. The movement of a head-mounted camera of a visual prosthesis patient would produce a transformation in captured images (optic flow) which can be extremely useful for segregating an image into component parts [32] and the rate of expansion can be used to calculate the amount of time before a collision will occur. By processing and presenting image sequences we should also be able to use fewer pixels for similar object recognition performance. Future work will concentrate on the mobility simulation and image sequence approach.

## ACKNOWLEDGEMENTS

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